

Online Short-Term Forecast of System Heat Load in District Heating Networks

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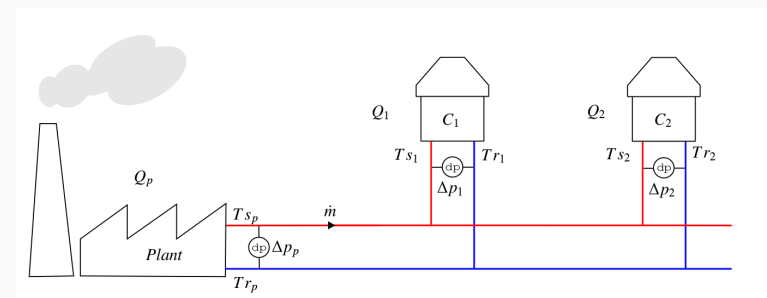
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Introduction

Background and goal



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Background and goal

Motivation Predicting energy use is essential for effective operation planning

Goal To accurately predict Heat Load requirement for a Housing network

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Parsing the title

Online Short-Term Forecast of System Heat Load in District Heating Networks

3

Parsing the title

Online Short-Term Forecast of System Heat Load in District Heating Networks

- Variable values are available each step of the model

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Parsing the title

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- 12 – 24h ahead

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Parsing the title

Online Short-Term Forecast of System Heat Load in District Heating Networks

- Variable values are available each step of the model
- 12 – 24h ahead
- Total heat load in central plant

3

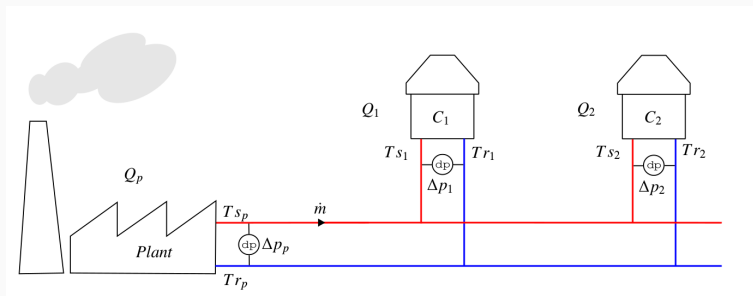
Parsing the title

Online Short-Term Forecast of System Heat Load in District Heating Networks

- Variable values are available each step of the model
- 12 – 24h ahead
- Total heat load in central plant
- Central plant distributes heat to network

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Parsing the title



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Online Short-Term Forecast of System Heat Load in District Heating Networks

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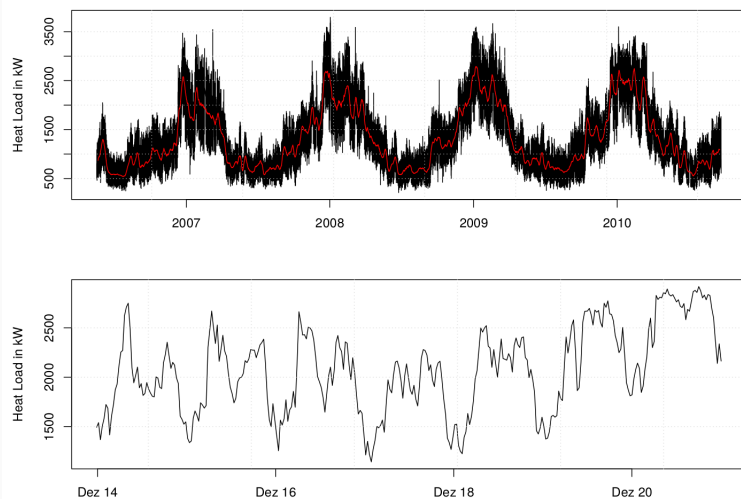
Material and Methods

Data

- System heat load
- 84 buildings in Tanheim, Austria
- Between 05/18/2006 and 09/22/2010
- 30-minute intervals

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Data



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Model

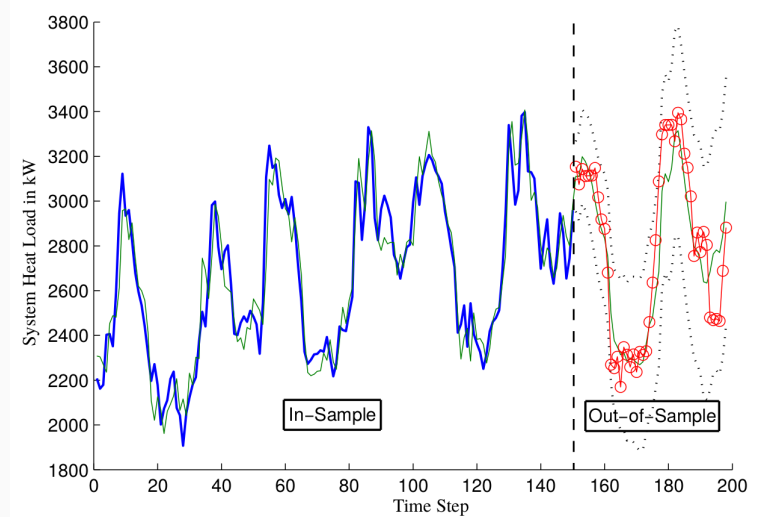
Seasonal AutoRegressive Integrated Moving Average (SARIMA) model

- Time-series
- Repeating patterns – trends
- Short-term correlations
- R and Matlab

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Results and Conclusion

Results



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Performance

- Accuracy determined by Mean Average Percentage Error (MAPE)
- MAPE calculated over 24 and 48 steps ahead (12h and 24h)
- Predictions compared to real data
- MAPE of 4.4% in one example

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Conclusion

- Positives**
- Results seem (very) good
 - Could potentially be used in other networks

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Conclusion

- Positives**
 - Results seem (very) good
 - Could potentially be used in other networks
- Negatives**
 - Scalability?
 - MAPE result only shown for only one example
 - More than 24h-ahead predictions?

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Questions?

SARIMA model

- S** *Seasonal*: repetitive patterns
- AR** *AutoRegressive*: variable is regressed on its own lagged values
- I** *Integrated*: values are replaced with the difference between their values and the previous values
- MA** *Moving Average*: regression error is a linear combination of previous error terms

MAPE boxplot

